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OPTIMIZATION OF THE DESIGN OF MODULAR PRODUCTION SYSTEMS

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ABSTRACT

The desire for more flexibility in manufacturing systems, especially when different products or many product variants are manufactured in one production system is leading to a move away from the manufacturing principle of classic line production to more flexible and workshop-oriented production systems, particularly in the automotive industry. One of the challenges in these so-called modular assembly or production systems is the system design, especially the allocation of activities to the individual production cells. One approach to improve this allocation is offered by simulation-based optimization. In this paper, a concept for simulation-based optimization of the design of modular production systems is presented and demonstrated by means of a small academic case study. Classical genetic algorithms and additionally the NSGA-II algorithm, which also allows multi-objective optimization, are used.

1 INTRODUCTION

The customer's increasing desire for more individuality in recent years presents companies with new challenges, which are further intensified by shorter innovation cycles and, as a result, often shorter product cycles as well as they are affected by external influences from the market, the state, etc. (Koren 2010).

Consequently, an essential requirement for modern production systems, especially in final assembly, is to be able to react flexibly to changing conditions while maintaining the economic efficiency of production for the sometimes large number of products or product variants (Feldkamp et al. 2019; Feldkamp et al. 2020; Hüttemann et al. 2016; Spath 2013; Wack 2019).

An insight gained particularly in the automotive industry, but not limited to it, is that classic line production systems are threatened to reach their limits, which means that a move away from this production principle towards more flexible systems must be investigated. Initial pilot projects have already been started in this regard (Göppert et al. 2018). In practice, various designations and variations can be found, such as "modular assembly" (Audi AG 2019), "flexi-line" (Mayer 2018) or "full-flex plant" (Daimler AG 2018). In the following, such concepts are subsumed under the collective term of modular production or assembly systems.

Such a modular production or assembly system consists of adaptable work stations (production cells) with specific tools, at which one or often several different production or assembly steps can be carried out and which are connected by automated guided vehicles (AGVs). Here, the system decides ad hoc, taking into account the existing technical restrictions and the individual task packages of the products or product variants to be manufactured, which path the product will take through the production system (Feldkamp et al. 2019; Feldkamp et al. 2020).

In addition to the major challenge of controlling such systems, the system design is also crucial for the performance of the production system as a whole. Current research focused almost exclusively on optimizing the control or control strategies of the AGVs, although it can be assumed that the system design has at least as great an effect on the overall performance of the system. Important points within the system design are, among others, the determination of the number of production cells as well as the distribution of tasks among them (Kern et al. 2016). A possible approach to solve such complex dynamic problems is simulation-based optimization, e.g. using genetic algorithms (Azadivar and Wang 2000). Such a concept and a small case study are the focus of this paper.

The structure of the paper is as follows: The introduction is followed by a definition and an overview of modular production/assembly on the one hand and simulation-based optimization on the other hand. Then the concept for simulation-based optimization of the system design of a modular assembly system is presented, which is demonstrated and validated in the next section by means of an academic case study. A chapter with conclusion and outlook concludes the paper.

2 RELATED WORK

2.1 Modular Production Systems

When using the concept of modular production systems, which is used here as a synonym for a number of similar terms, the classic principle of flow production is dissolved in favor of a more job-shop-alike production scheme. The production takes place in the modular assembly on production cell or stations, often the final assembly of automobiles is considered. These can perform various tasks in a very flexible manner, depending on the product to be manufactured or the product variant. The individual tasks (process steps) can be very different and are not bound to a globally uniform system cycle time, as shown in Figure 1. The transport of workpieces between the production cells as well as the transport of material is handled by AGVs (Feldkamp et al. 2019; Hüttemann et al. 2016; Kern et al. 2017).

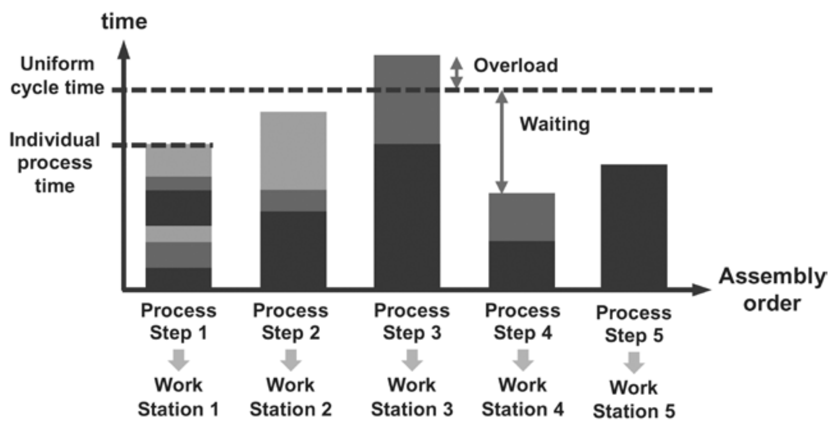

Figure 1: Individual process times vs. uniform cycle time (Greschke et al. 2014).

It should be noted that no fixed sequences of work steps are defined, but the choice of the next work step is made based on the next steps that are technically possible for the specific product, the system design, and the current state of the production system. The definition of the technically possible next steps is usually done by means of priority graphs. In summary, modular assembly is characterized by the following features:

- Decoupled workstations with individual cycle times
- Multiple activities / capabilities per production cell
- Flexible material flows by means of AGVs (Hüttemann et al. 2016; Kern et al. 2017).

The current state of a modular assembly system, which is an essential database for the control system, can be described in various complex ways. The number of possible parameters is large and can range from data of the buffers and machines, e.g. queue lengths, to data on the own production progress, to complex observations of all other products / AGVs in the system, including their current position, actual production step or even their planned activities.

The concept of modular production systems leads to an inherent flexibility of production both in the form of resource flexibility, i.e. one station can perform different tasks, and in the form of route flexibility, since products can be produced in different work step sequences or, even with the same sequences, on different production cells if necessary.

These flexibilities are largely determined by the design of the modular production system, where various design dimensions are relevant. Thus, in addition to the basic layout, i.e., the basic spatial structure of possible manufacturing cells, the tasks and activity distribution among the individual cells must also be considered in particular. Thereby, the scope for decisions is quite large. First, it has to be decided how often an activity should occur redundantly before it can be decided on which cell(s) the activity should be offered. In practice, this decision is limited by a large number of technical and organizational restrictions, e.g., technical parameters may prohibit certain combinations of activities from being performed on a production cell. Furthermore, the number of available AGVs and their routing algorithms as well as the selected material supply concept also have a major influence on the overall performance of the system.

In some publications it is shown that such complex systems like modular production systems are hardly controllable without the use of modeling and simulation methods (Feldkamp et al. 2019; Filz et al. 2019; Mueller et al. 2018; Schönemann et al. 2015).

2.2 Simulation-based Optimization

Simulation is an established tool for modeling, planning and controlling production systems. The coupling of simulation and optimization algorithms is a very common and frequently investigated method. The goal is to find the best (or at least a good) combination of settings (factors) for a system that is being investigated. In the process of simulation-based optimization, factor values (and thus system configurations) are set purposefully by the optimization algorithm, and the simulation is then used to determine the fitness or the target value(s) while setting the factor values (Amaran et al. 2016; Beham et al. 2008; Fu 2015; März et al. 2011). In the context of simulation-based optimization, a broad range of different optimization algorithms is used in the literature. The choice of the appropriate algorithm depends strongly on the application to be investigated (Amaran et al. 2016; März et al. 2011). In corresponding publications frequently used algorithms are for example: genetic algorithms (GA), simulated annealing, tabu search, scatter search, ant algorithms as well as the particle swarm optimization (Amaran et al. 2016; Fu 2015).

For the optimization of the design of modular assembly systems, different algorithms were examined by the author. However, in the context of this contribution it is limited to genetic algorithms, since these produced stable and good and/or very good solutions for all test cases. Furthermore, genetic algorithms have generally preferable properties, they are widespread, easy to use, tools are available, the results are well comprehensible, moreover, e.g. with the non-dominated sorting genetic algorithm II (NSGA-II) variants of the algorithms are available, which also allow multi-objective optimization (Deb et al. 2002; Deb 2011; Fu 2015; Gerdes et al. 2004).

In general, genetic algorithms are algorithms of the class of evolutionary algorithms. Here, single solutions (individuals) are described by their factor values (genes) and can be evaluated e.g. by means of simulation runs with respect to a target value (fitness). To start the optimization, a defined set of random solution candidates is generated (1st generation of the population) and their fitness values are determined. Then the following steps are performed for the current population (generation) until a termination criterion is reached (e.g. certain elapsed time, certain number of generations reached, no improvement achieved in the last steps):

1. recombination/mutation: addition of new solution candidates by combination of two individuals of the current generation or random modification of such a candidate.
2. evaluation: determination of fitness values for all new solution candidates

3. selection: determination of the next generation of the population by selection of the best solution candidates.

For further details on genetic algorithms, especially the basic operations, please refer to the corresponding literature, e.g. (Gerdes et al. 2004; Holland 1992).

As already mentioned, the non-dominated sorting genetic algorithm II (NSGA-II), for example, also allows multi-objective optimization. In the context of the optimization of the design of modular assembly systems, often problems with several possibly competing or even contradictory objectives, e.g. maximization of the utilization of the production islands vs. minimization of the average lead time of the products, need to be solved. The NSGA-II algorithm, which is frequently used for such multi-objective optimization, supports the finding of such compromise solutions (so-called pareto-optimal solutions). Pareto-optimal solutions are solutions in which one target variable cannot be further improved without degrading another (non-dominated property). The NSGA-II algorithm now evaluates currently non-dominated solutions particularly well in the context of selecting the fittest factor combinations (Yusoff et al. 2011). From the list of pareto-optimal solutions generated at the end of the optimization process, the end user can select the most suitable solution for the use case, based on his own preferences.

For details of the algorithm, please refer to the relevant literature, e.g., Yusoff et al. 2011.

3 CONCEPT FOR SIMULATION-BASED OPTIMIZATION OF THE SYSTEM DESIGN OF MODULAR ASSEMBLY SYSTEMS

The concept for simulation-based optimization of the system design of modular assembly and production systems (cf. Figure 2) has been designed as generically as possible in order to be usable in many applications.

The basis is a suitable simulation model with the corresponding basic layout of the production, which has suitable interfaces, among others, for setting factor values and reading out key figures; all other framework conditions as well as the parameters of the optimization are described via stored data structures that can be adapted at any time.

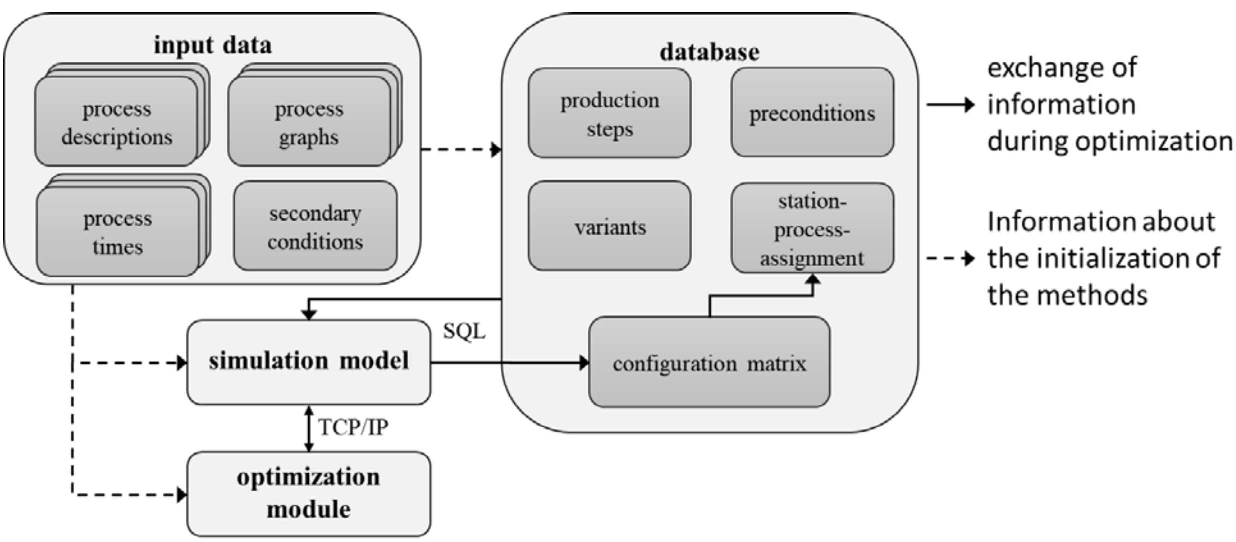

Figure 2: Basis concept for simulation-based optimization of system design for modular product systems.

The aim of the concept is to support the planner of modular production or assembly systems in assigning activities/capabilities to production cells. Indirectly, the number of production islands required can also be determined, whereby a maximum number is specified by the layout and the actual requirement results from the maximum number of stations that may not be assigned activities.

As shown in Figure 2, the concept is based on four main components: input data, database, simulation model, optimization module.

configurations_matrix

	production_step	station1	station2	station3	station4	station5	station6
1	A	1	1	1	1	0	0
2	B	1	1	1	1	0	0
3	C	1	0	0	0	0	0
4	D	1	1	1	0	0	0
5	E	1	1	1	0	0	0
6	F	1	1	0	0	0	0

Figure 3: Example of a configuration matrix.

As already mentioned in Section 2.1, the most important input data are the required process steps of the individual products or product variants, their dependencies on each other in the form of process graphs (cf. Figure 5), the process times, and secondary conditions such as the exclusion of certain activities at a station (incompatibility) by means of compatibility matrices (cf. Table 2), the maximum number of AGVs available, and the maximum number of activities allowed per production cell. Some constraints are currently fixed set in the prototype. For example, it is specified that each required activity must be assigned to at least one production cell in order to represent a valid solution. Furthermore, it is assumed here that each AGV transports only one product and that processing takes place inline, i.e. processing takes place on the AGV, so an AGV (if present) is allocated when the product arrives in the system and is not released again until it has been completely processed. The AGVs are controlled according to a simple heuristic, in which the shortest possible waiting queue is always chosen. Each production cell can also process only one product at a time (no parallel stations) and had a additional buffer for one AGV.

The input data are first transferred to tables in a database to facilitate further processing. In addition, the system designs currently considered by the optimizer are stored in further tables (configuration matrices). Such a configuration matrix contains the assigned activities for each station. An example of such a matrix is shown in Figure 3. Among other things, the information stored in the database component was used for initializing the simulation model. In this paper, for the simulation, an agent-based approach implemented in AnyLogic is used, which was already used as a comparative implementation in (Feldkamp et al. 2019).

As the optimization tool, HeuristicLab (HeuristicLab 2021) was chosen, because it supports many optimization algorithms, such as classical GA and the NSGA-II algorithm. In addition the optimization problem is easy to parameterize, and extensions can be easily implemented using C# programming. Extensions were developed for the communication of the optimizer with the simulation model via TCP/IP, as well as for the verification of the constraints and the necessary correction mechanisms. Currently available are the following six target functions, which can be supplemented by additional ones at any time:

- Max. throughput,
- Max. utilization of the assembly stations,
- Min. of the total distance covered by the AGVs,
- Max. of the utilization of the AGVs,
- Max. of flexibility, and
- Max of the route flexibility.

The schematic flow of the optimization is shown in Figure 4.

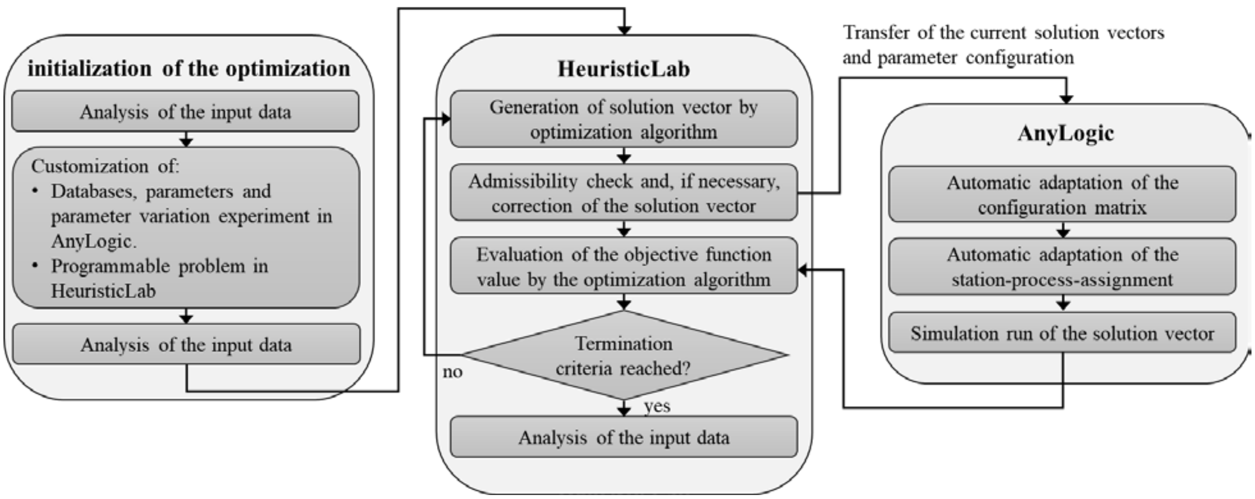

Figure 4: Schematic flow of the optimization.

4 CASE STUDY

For the evaluation of the concept, different scenarios were defined and examined by means of different optimization methods, objective functions etc. In this paper, one of the investigated fictitious production systems is used as an illustration.

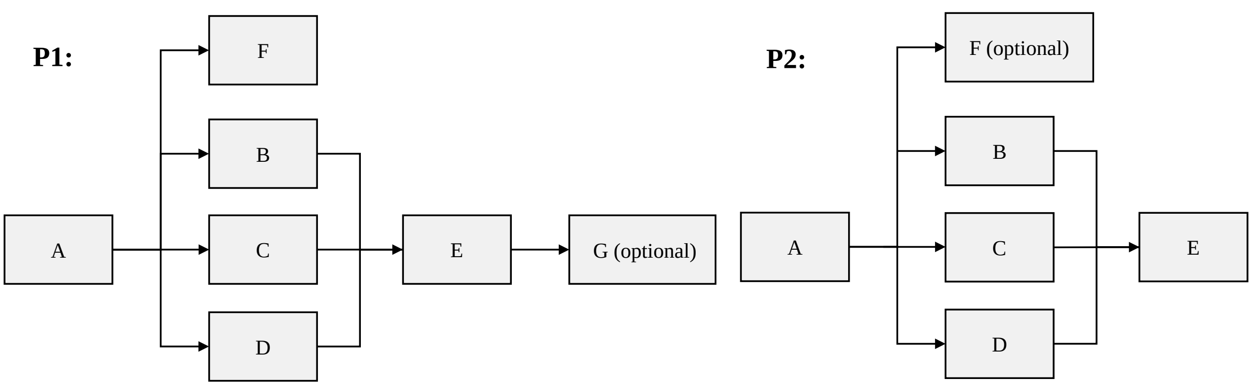

Figure 5: Process graphs of the products P1 and P2.

In this system two products (P1 and P2) are manufactured in different variants. A total of 7 different activities (A to G) are to be distributed on up to 9 production cells (station 1 - 9). The corresponding priority graphs of the production process for each of the products can be seen in Figure 5. Product variants result from the optional activities. The triangularly distributed process times of the individual activities are listed in Figure 5.

A production order for one of the product variants arrives in the system every 120 seconds. The distribution of the products or product variants is the same for all.

Table 1: Process times (triangular distributed).

activity	Process time in seconds (min value, most probable value, max value)
A	90, 100, 110
B	180, 200, 220
C	50, 70, 90
D	60, 80, 100
E	200, 220, 240
F	80, 100, 120
G	90, 100, 110

Among other things, some incompatibilities between individual activities were defined as constraints; these can be seen in Table 2. The process compatibility matrix is to be read in such a way that activity combinations with the value 0 are excluded at a production island, here e.g. the activities A and F. The maximum permissible number of activities on a production island was set centrally to 4.

Table 2: Process compatibility matrix.

	A	**B**	**C**	**D**	**E**	**F**	**G**
A	0	1	1	1	1	0	0
B	1	0	1	1	1	0	0
C	1	1	0	1	1	0	0
D	1	1	1	0	1	0	0
E	1	1	1	1	0	1	1
F	0	0	0	0	1	0	1
G	0	0	0	0	1	1	0

The system outlined here was optimized using a classical genetic algorithm (GA) and the NSGA-II-algorithm. For both algorithms, the following values were used for the hyperparameters:

- Population size: 100
- Number of generations: 6
- Simulation duration: 2 hours
- Recombination method: Rounded Average Crossover
- Recombination probability: 90%.
- Mutation method: Uniform Some Positions Manipulator
- Mutation probability: 5

In addition, the Proportional Selector was used as the selection method for the classic GA and the Crowded Tournament Selector for the NSGA-II.

The selection of the hyper parameter values used here was based on the values recommended in the literature for similar problem classes or on comparisons of different parameterizations, which were made during the development of the prototype.

The optimization with the GA was performed twice with 2 conflicting objectives, first the throughput of the overall system and second the utilization of the production cells, the results can be seen in Table 3.

Table 3: GA solutions for target throughput and cell utilization.

objective	number of AGVs	cell 1	cell 2	cell 3	cell 4	cell 5	cell 6	cell 7	cell 8	cell 9
throughput	5	A, B	C, E	D	F	G	E	E	-	-
cell utilization	4	A, C	B	D	F	E, G	-	-	-	-

The genetic algorithm achieved a value of 18 products for maximizing the total throughput and achieved a value of 32.11% utilization when using the total utilization of all cells as the target size. In subsequent tests carried out with the solutions, it was found that the other indicator, which was not used as a target value, showed significantly worse values: the utilization in the solution with maximum total throughput was less than 29 %, and when optimizing the utilization, no more than 16 products were produced. In the comparison of the biggest differences of the solutions it is noticeable that with the optimization of the throughput in contrast to the maximization of the utilization, activity E occurs three times in the system. This can be explained by the fact that the process time of this activity is the highest in the system (see Table 1), which may represent a potential bottleneck in the system. It is remarkable that regardless of the used row size not all max. 9 cells are used, so the use of 2 or even 4 cells can be omitted.

What is also to be recognized, however, is that even for this quite simple application case, a consideration of several target variables in parallel is quite reasonable. This can be achieved by using the NSGA-II algorithm.

First, the total throughput and simultaneously the total utilization of the production cells were examined as objective functions. The idea behind the choice of objective functions was to find solutions that achieve the highest possible throughput, but do not simply allocate all activities a maximum number of times and ideally require as few cells as possible.

The results are shown in Table 4 (left part). It can be seen that throughput is highest in pareto optimum A2, with at least one activity assigned to all production cells. Pareto optimum A3, on the other hand, appears to be a good compromise between the number of production cells required (6 of the max. 9) and, compared to the other solutions, their utilization as well, and throughput, which is moderately lower than in pareto optimum A2.

Furthermore, it can be seen that individual pareto optimal solutions are quite comparable to the shown solutions of the classical GA. Here, too, it can be seen that multiple availability of activity E on multiple cells leads to increased throughput. In addition, it appears that activity B also represents at least a partial bottleneck, since it was also assigned twice in the solution with the highest throughput.

In a further experiment, the NSGA-II algorithm was also used to optimize the overall throughput and the route flexibility (number of theoretically possible routes through the production system, which the product can take until completion). The background of this choice of objective functions is to find a system design that has a good throughput as a necessary condition on the one hand, but also a high flexibility on the other hand. One assumption is that such a high flexibility may ensure a certain robustness against disturbances in the system, but also against fluctuating distributions of the frequencies of the two products. Furthermore, it is assumed that, if necessary, the extension of the system, e.g. when introducing further products with similar production steps, can be realized more easily.

As can be seen from Table 4 (right part), solutions were also found here which realize a high throughput. For example, a throughput of 19 was achieved in the Pareto optimum B2, which is overall the best solution in terms of throughput of all the tests listed here. It should be noted, however, that this solution has a rather low route flexibility (211 compared to the maximum of 548) compared to the other solutions. In general and somewhat surprisingly, it can be seen that solutions with a high route flexibility apparently lead to rather moderate throughputs. In addition, as was also to be expected, high route flexibility (e.g., in pareto optimum B1) goes hand in hand with the assignment of quite a lot of activities per station and the use of as many stations as possible.

Table 4: NSGA-II solutions for objective throughput / cell utilization and throughput / route flexibility.

	objective: throughput and cell utilization			**objective: throughput and route flexibility**			
	pareto optimum A1	pareto optimum A2	pareto optimum A3	pareto optimum B1	pareto optimum B2	pareto optimum B3	pareto optimum B4
throughput	15	18	17	13	19	15	17
utilization	32,14 %	28,81 %	31,85 %	not listed			
route flexibility	not listed			548	211	454	267
number of AGVs	5	5	5	5	5	5	5
Station 1	F	A	F	A, C, D, E	A	B, E	A
Cell 2	G	C	G	B	B	D, E	C
Cell 3	-	E	-	E, F, G	F	E, F, G	F
Cell 4	-	G	-	A, C, D, E	C	D	E
Cell 5	-	D	E	A, D	D	A, E	E
Cell 6	-	F	-	B, C, D	E	G	B, E
Cell 7	E	B	E	E, G	G	D, E	B, D
Cell 8	A, B	A, B	A, B	E, F, G	-	A, B, C	E
Cell 9	C, D	C, D	C, D	B, C	-	C	G

In summary, it can be said that depending on the preferences of the decision maker, very different solutions could become relevant. If we assume that a high throughput is desirable and that not using entire production cells saves costs and is also positive in the case of possible expansions, then the Pareto optimum B2 of the NSGA-II optimization is to be preferred according to the target variables throughput and route flexibility. This solution also achieves the highest throughput of all the solutions identified here with 19, and this is despite the fact that two of the possible production cells are not required; only the route flexibility identified is rather low compared to the other solutions listed here. If, on the other hand, the use of as many cells as possible is to be dispensed with (while maintaining a solid system performance), then the solution shown for the GA with the objective function of maximizing utilization is to be preferred. Here, a total of 4 of the 9 cells were not needed for the production of the two products.

The use case used here serves only to show the potential offered by the optimization of the system design. Critically, real-world scenarios are more complex, but initial experiments with more complex use cases indicate that the concept scales well and that there is considerable potential for improvement in more complex systems and at higher workloads.

5 CONCLUSIONS AND FUTURE WORK

In this paper, a concept for simulation-based optimization of the system design of modular production systems using a classical GA and the NSGA-II algorithm was presented, which in particular supports a good activity assignment to the individual manufacturing cells. The specifics of modular production systems were first discussed before describing the basic features of simulation-based optimization, in particular using genetic algorithms and the multi-objective NSGA-II algorithm.

A simple academic case study was used to demonstrate the concept and its prototypical implementation. It could be shown that optimization potentials do exist and could also be raised with the concept.

In the future, various directions for further research are conceivable. For example, further optimization algorithms as well as the extension or adaptation of constraints, e.g. space requirements of activities, are possible. Furthermore, adjustments to the correction mechanisms for invalid solutions are also a possible research topic. Finally, other design dimensions of modular production can be included, for example, consideration of material provisioning concepts, alternative basic layouts, or different control algorithms would be possible. Finally, it would also be exciting to test the concept in real-world scenarios.

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